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Review of methods and Algorithms in Deep Learning

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Abstract:

Deep learning (DL) is playing an increasingly important role in our lives. It has already made a huge impact in areas, such as cancer diagnosis, precision medicine, self-driving cars, predictive forecasting, and speech recognition. The painstakingly handcrafted feature extractors used in traditional learning, classification, and pattern recognition systems are not scalable for large-sized data sets. In many cases, depending on the problem complexity, DL can also overcome the limitations of earlier shallow networks that prevented efficient training and abstractions of hierarchical representations of multi-dimensional training data. Deep neural network (DNN) uses multiple (deep) layers of units with highly optimized algorithms and architectures. This paper reviews several optimization methods to improve the accuracy of the training and to reduce training time. We delve into the math behind training algorithms used in recent deep networks. We describe current shortcomings, enhancements, and implementations. The review also covers different types of deep architectures, such as deep convolution networks, deep residual networks, recurrent neural networks, reinforcement learning, variational auto encoders, and others.

Keywords: Deep learning, CNN, RNN, NLP,DNN, Machine learning, Artificial intelligence

Introduction

Neural Network is a machine learning (ML) technique that is inspired by and resembles the human nervous system and the structure of the brain. It consists of processing units organized in input, hidden and output layers. The nodes or units in each layer are connected to nodes in adjacent layers. Each connection has a weight value. The inputs are multiplied by the respective weights and summed at each unit. The sum then undergoes a transformation based on the activation function, which is in most cases is a sigmoid function, tan hyperbolic or rectified linear unit (ReLU). These functions are used because they have a mathematically favorable derivative, making it easier to compute partial derivatives of the error delta with respect to individual weights. Sigmoid and tanh functions also squash the input into a narrow output range or option, i.e., 0/1 and −1/+1 respectively. They implement saturated nonlinearity as the outputs plateaus or saturates before/after respective thresholds. ReLu on the other hand exhibits both saturating and non-saturating behaviors with $f(x) = \max(0,x)$. The output of the function is then fed as input to the subsequent unit in the next layer. The result of the final output layer is used as the solution for the problem.

Neural Networks:

Neural Networks can be used in a variety of problems including pattern recognition, classification, clustering,

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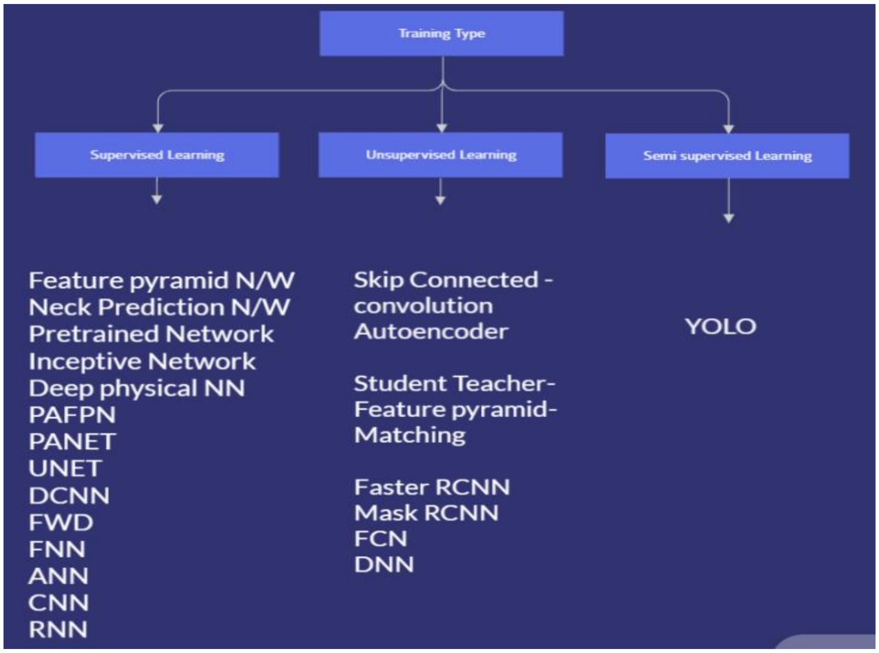
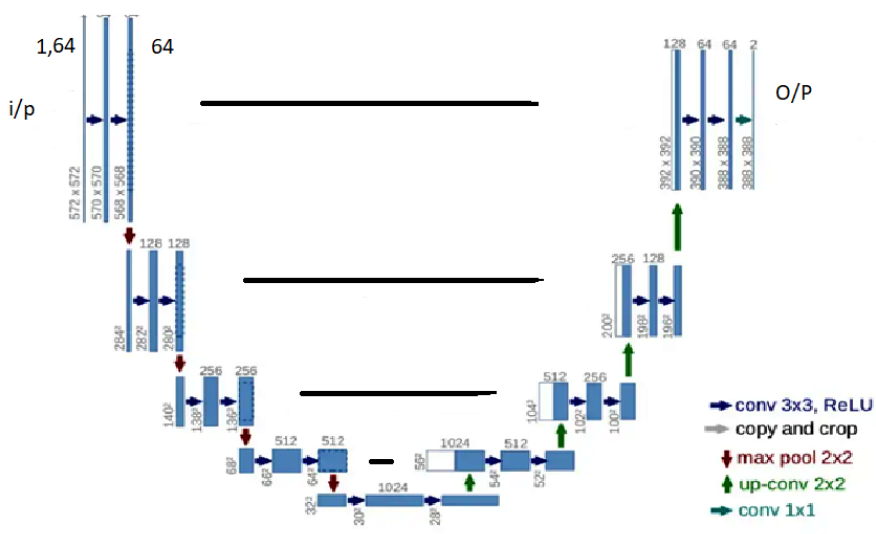
dimensionality reduction, computer vision, natural language processing (NLP), regression, predictive analysis, etc. As the research progress in this field, many neural networks took birth and now frequently used for development and further research process. These are classified with respect to the type of training they received, majorly there are three types of training given to a neural network i.e. supervised, unsupervised, semi supervised.



1.**U-NET Architecture:**



U-NET Architecture

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Unet has made its evolution from traditional CNN and was designed and came in process in 2015, as biomedical image processor. As per the general idea of working in a CNN network is as part of input image goes in the network and a predetermined label comes as output but in case of biomedical images one not only has to determine the disease but also the accurate affected area which is abnormal.

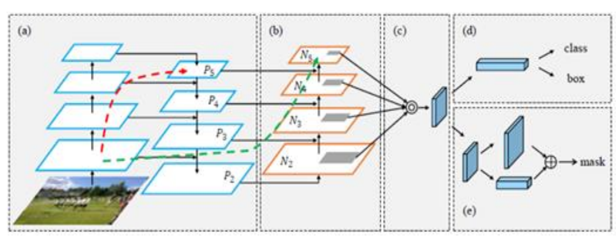
UNET is able to classify each and every pixel in the image so both input image and output are same in size. It can clearly make a difference between borders and image pixels. If the input image pixel size is (2*2) then the output pixel will also be (2*2).

UNET Architecture is symmetric both sides as depicts in image, the left side is contracting and right side is expensive part. Left side is made up of general convolution however right side is made up of transposed form of 2d convolution plates.

Layers	Contracting Path	Expensive Path
	Conv1	Deconv4
	Conv1	Uconv4
	Pool1	Uconv4
	Pool1	Uconv4
		Uconv4
	Conv2	
	Conv2	Deconv3
	Pool2	Uconv3
	Pool2	Uconv3
	Conv3	Uconv3
	Conv3	Uconv3
	Pool3	
	Pool3	Deconv2
		Uconv2
	Conv4	Uconv2
	Conv4	Uconv2
	Pool4	Uconv2
	Pool4	
		Deconv1
	Middle-	Uconv1
	Convm	Uconv1
	Convm	Uconv1
		Uconv1

2. PANET:

PANET is the soul of YOLOV4 model and brought to it for the purpose of image segmentation by using the spatial information. PANET is useful because it is able to contain spatial information in accurate manner which then used in pixel localization in formation of mask.



Bottom up path augmentation:

Feature complexity goes up as the image goes through multiple layers of network and spatial resolution goes down because of this mask at pixel level not identified accurately. PANET uses an additional bottom up path

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with the use of lateral connections from lower steps all the way up to top layers. This is considered as short method covering only 10 layers. It is shown in the diagram in red dotted line.

Adaptive Feature Pooling:

Old technique Mask-RCNN was using features from only one stage to make prediction. It was using align pooling with ROI to take features from top layers if it was a big region. Sometimes it was not as accurate as the result should be because when minute proposals as close as 10 pixels are assigned to 2 different layer, however in fact they are not so different but very similar to each other.

In order to overcome this problem PANET takes features from all layers and the decision to select feature is left on the network itself. In each of the feature it will perform ROI align operation to take out feature for object, which then succeeded by max fusion technique(element wise) to give the network a free hand to pick up new features.

3. Feature Pyramid Networks:

To locate small objects using different scaling technique is hard, one can try to use a same image pyramid on a different scale to see objects clearly but process of many images simultaneously is time consuming and takes huge memory .so we can use this to push the accuracy at a very high level in certain cases only, where we are very particular on accuracy and are ready to compromise in other parameters. In addition to this a pyramid of features can also be created and used for object detection purpose but feature maps associated with image layer made up of low level structures are not very effective for accurate detection.

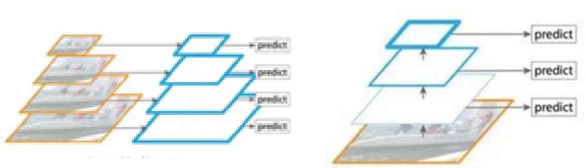

Image Pyramid　Feature Map Pyramid

Fully Connected Fusion:

In FCN- Fully Connected Network was used instead of fully connected layers since it saves the important spatial information and bring down parameter number with in the network. But because parameters are onto share basis, it is difficult for model to learn pixel location in order to make prediction. By default pictures will be in majority where roads are shown in bottom part and sky is shown in top part of picture.

PANET easily put on neighbor layer for mask prediction by using adaptive feature pool moreover this method is a little twisted when this network was employed in YOLOV4 where in place of addition of layers concatenation was applied to improve the efficiency.

Feature Pyramid Network(FPN) are designed keeping in mind both the accuracy and speed of operation.FPN can replace other feature extractors and generate multiple feature map layers with higher quality information.

Data Flow:

FPN composes of two pathways bottom-up and top-down, in **bottom-up** pathway it uses RESNET to construct the way which consists of many convolution modules within it, and each module consists of many layers. As we move towards the top, spatial dimension decreases. The output of each module get labeled and further used in top down path. In **top-down** approach nearest neighbor up sampling is used to up sample the previous layer by 2. Then again convolution of 1*1 is applied to corresponding feature maps, finally we add them element wise and merge all layers with convolution of 3*3.

4. PAFPN- Path Aggregation Feature Pyramid Network:

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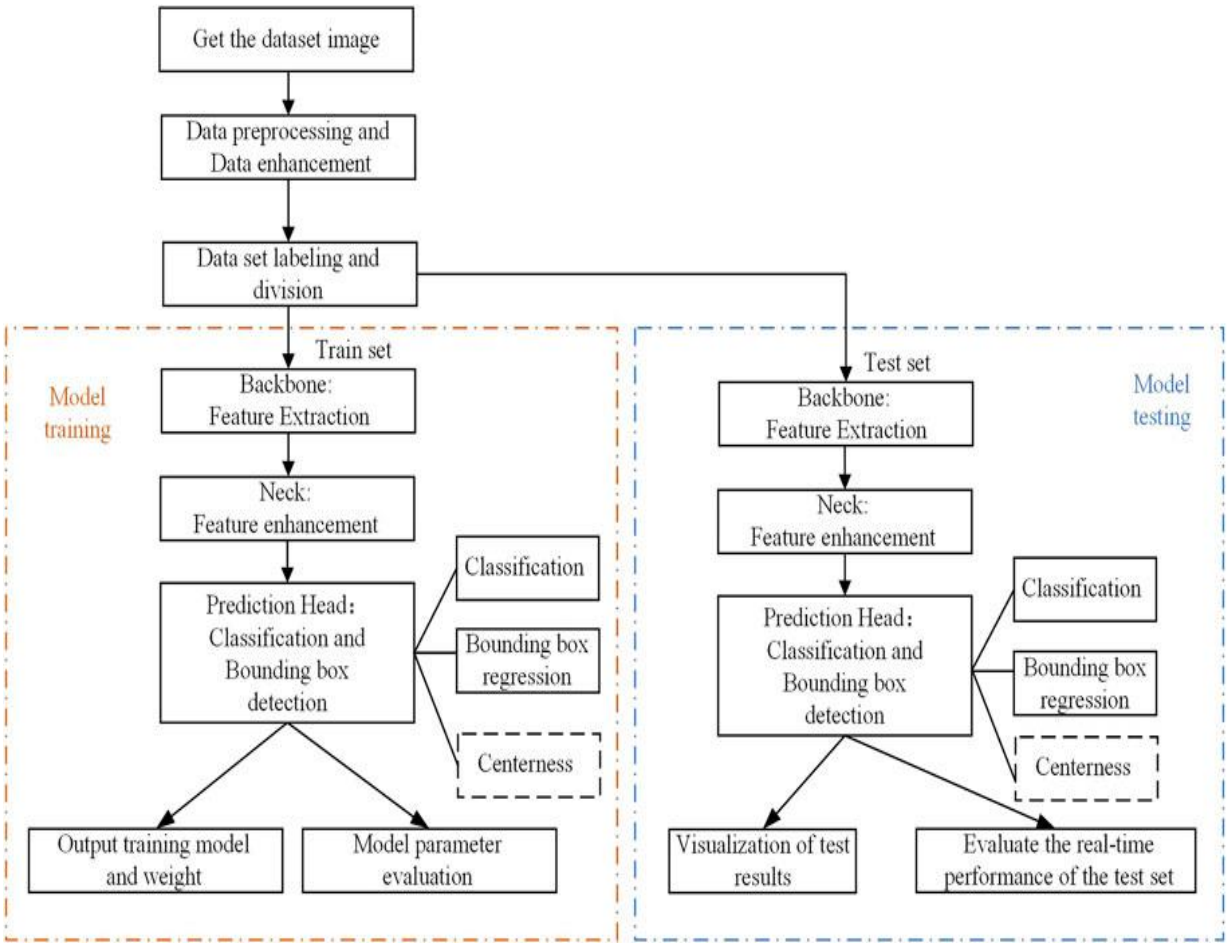
This particular network was designed specifically for PCB defect detection. Keeping the importance of safety and reliability of electronic components this network was designed to detect the defected PCB wafers from the produced pool of components.

PAFPN is single stage light weight based on dual attention mechanism and path aggregation. As compared to the already available present methods for object detection like faster R-CNN and YOLO V3 this network has the inference time reduced with 17.46 ms which is very suitable for industry needs.



Highlights of PAFPN:

1. The base model used is single stage object detection (FCOS) model, which reduces proposal region detection and is very simplified structure helps in performing real time detection. As shown in flowchart a backbone neural network (lightweight) is used for commonly used ResNet101 and FCOS replacement.

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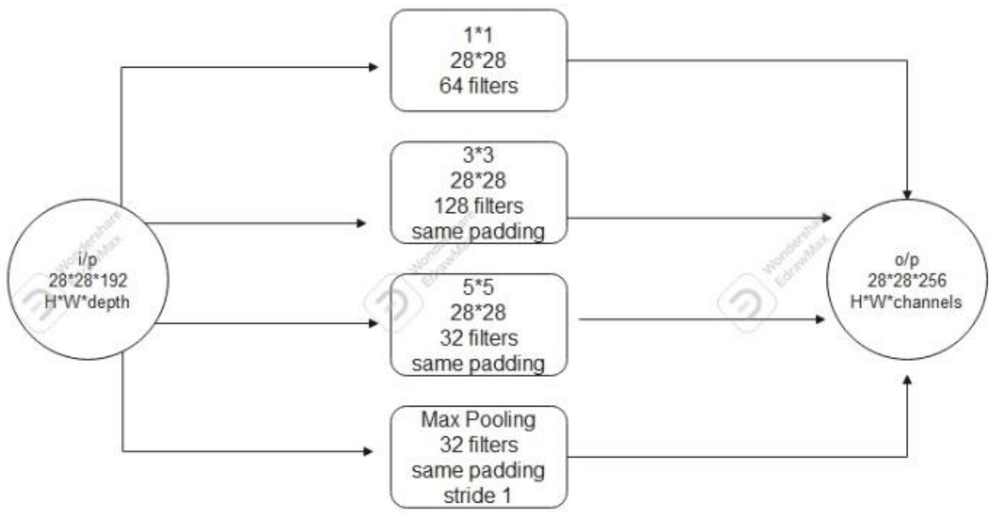
2. Path aggregation network method is applied in order to solve the lightweight backbone problem. Further in the Neck part feature enhancement and feature fusion is applied which shortens the information path while using low level information to assist FPN.
3. For accurate detection for small size defects bounding box regression loss function applied. IOU function can see the overlap rate, ratio between the predicted box and ground truth box and distance is minimized to make the conversion process faster and regression is stable.

5. Inception Network:

This network is a deep neural network designed with the architecture which consists of repeating components called as Inception Modules.



Design of inception network:

1. A deep neural network which is high performer should be large in order to give best results, more the layers more the accuracy of the network.
2. CNN works efficiently when they extract features at different scales. Just like a biological human cortex works by identification of pixels at different scales. That's why it is necessary to have more number of layers in network.
3. As per Hebbian principle, neurons that fire together, wire together.

Inception module consists of following components:

1. Input layer
2. 1*1 convolution layer
3. 3*3 convolution layer
4. 5*5 convolution layer
5. Max Pooling layer
6. Concatenation layer

6. Pre-trained network:

It refers to those networks when we train the model first on one task and collect results from it then we further use this extracted parameters to train another model for a different objective or task, then the first model is called pre trained model and it greatly helps in bringing down the latency and reduce the time, as well as gives more accuracy.

Steps to pre-train a network:

1. Let us say we already have a ML model model1 and dataset A and dataset B.
2. Train model1 with dataset A
3. Initialize some parameters of model1
4. Train it model1 on dataset B

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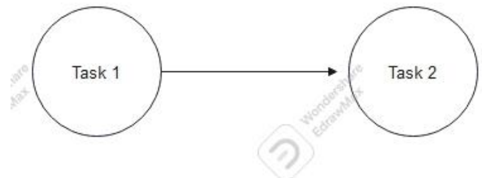
Applications of Pre-trained network:

1. Transfer Learning – using knowledge learned from one problem to use in another object.



2. Classification
3. Feature Extraction

Pros of Pre-trained network-

1. Ease of use

2. Quickly optimize

3. Need less data

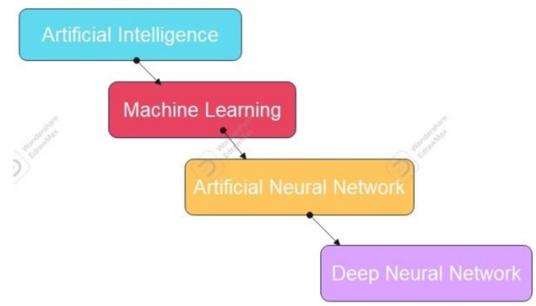
Cons of Pre-trained network-

One pre-trained model which is trained in a particular domain cannot be used in different domain for training purpose otherwise it will give us horrible accuracy.

Example: VGG-16, Inceptionv3, ResNet50, EfficientNet

7. DNN(Deep Neural Network):

Deep neural network is made up of ANN when multiple hidden layers are introduced in between the input and output. This kind of network is used to receive a particular set of input, making progressively complex mathematical calculations on them then give output as solution to real world problems such as classification, object detection etc.



8. Faster RCNN:

Faster RCNN is advanced version of fast RCNN in which Regional Proposal Network (RPN) – a fully convolution network generates proposals with different scales and aspect ratios. This uses and implement neural network with attention to suggest the object detection where to find the required features.

It doesn't use pyramids of multiple images or filters but uses an anchor box with a special scale and aspect ratio. With multiple anchor boxes many number of scales and aspect ratios exist for a single region. This can work as pyramid of anchor boxes. Where each region is mapped with anchor box. These convolution mathematical computations are feeded to all RPN and Fast RCNN to bring computational time.

Faster R-CNN works as mentioned below:

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1. RPN would generate regional proposal.
2. A feature vector of specified length is extracted for all the proposals within one image while using ROI pool layers
3. Those features are then given class of FastRCNN
4. Class scores and bounding boxes are returned.

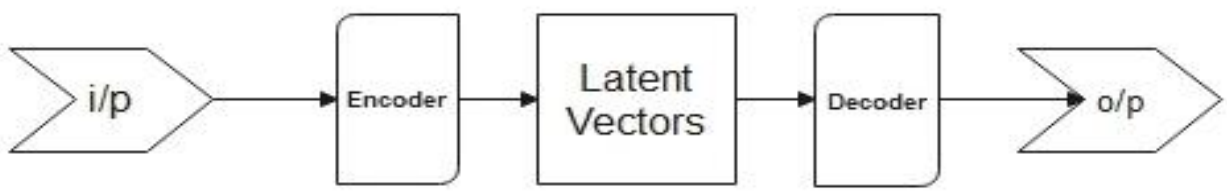
9. Skip Connected Convolution Auto encoder:

A network like auto encoder, at one end it encodes the given input to low dimensional latent space and at another end it performs the decode operation. It is mostly used for unlabeled data where we need to extract general useful features in the unsupervised fashion.

It consists of two parts:

1. Encoder – convert input data in low dimensional latent vectors
2. Decoder – convert the latent vectors in original data (Reproduction)

To deal with 2D images we use auto encoder with convolution layers this is called **convolutional auto encoder**. Convolution is the basic concept of CNN which are used to analyze the image or visual data where multiple layers of parameters are used with learnable filter.When deep neural networks begins to converge degradation problem starts to affect. As the depth of network increases this problem doesn’t let the accuracy go beyond a certain level. To solve this problem we use skip connection between the encoder and decoder. This enables the network to converge to a best optimum.



Architecture of Skip Connected Convolution Network:

Layers	**Kernel(channels, filter size)**	**o/p**
Imput		400,400,3
Conv1	64,5*5	400,400,64
MaxPooling 1	2*2	200,200,64
Conv2	64,5*5	200,200,64
MaxPooling 2	2*2	100,100,64
Conv 3	128,3*3	100,100,128
MaxPooling 3	2*2	50,50,64
Conv 4	128.3*3	50,50,64
MaxPooilng 4	2*2	25,25,128
Conv 5	128,3*3	25,25,128

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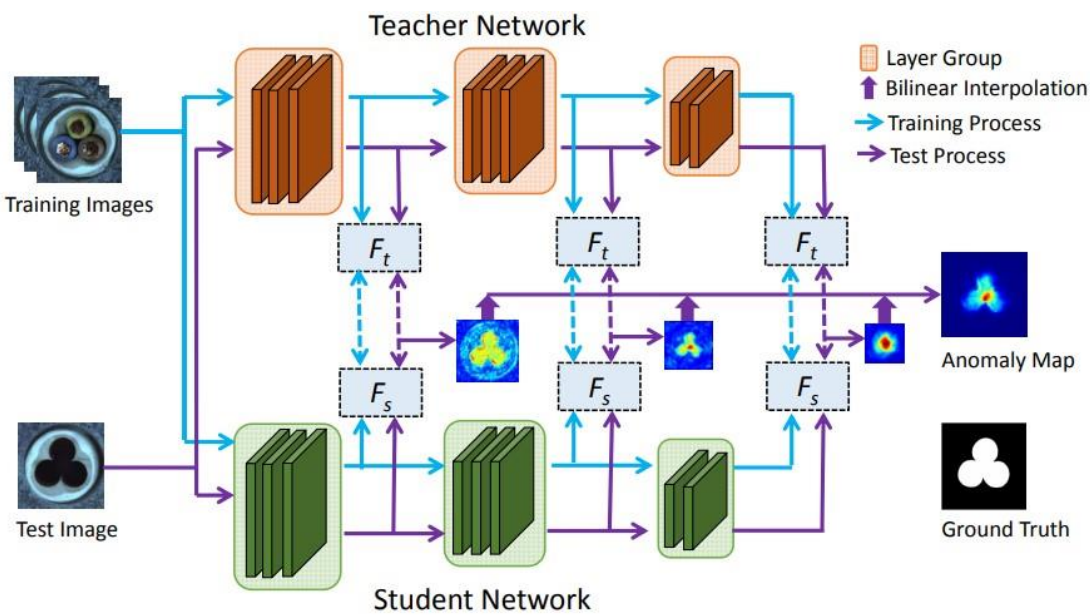
UpSampling 1	2*2	50,50,128
Conv 6	128,3*3	50,50,128
UpSampling 2	2*2	100,100,128
SkipConnection 1	-	UpSampling2+Conv 3
Conv 7	64,5*5	100,100,64
UpSampling 3	2*2	200,200,64
SkipConnection 2	-	Upsampling 3+conv 2
Conv 8	64,5*5	200,200,64
UpSampling 4	2*2	400,400,64
SkipConnection3	-	UpSampling4+conv 1
Conv 9	3,3*3	400,400,3

10.Student-Teacher Feature Pyramid Matching:
A pre trained strong model is taken for image classification as teacher and distilled into a student network with similar architecture learning the variable anomaly free image, this step transfer the very important features. Further the integration of multiple scale feature scale matching in the framework, which then let student teacher network receive a mix of multiple level knowledge from feature pyramid.



Algorithms

Various algorithms used in Deep learning networks are as follows:

Sr.No.	Algorithm	Description
1	YOLO	• Used for object detection • Very fast (45FPS) • Uses end to end neural network predicting bounding boxes and class
2	YOLOv2	• Introduced for small object detection in group

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		• To enhance mean Average Precision • Uses batch normalization
3	YOLOv3	• Uses complex DarkNet-53 • 106 layer neural network • Can predict on 3 scales
4	YOLOv4	• weighted residual connection, cross mini batch normalization • cross stage partial connections • self adversarial training, mish activation
5	YOLOv4-MN3	• Uses lightweight network MobileNetv3 • MobileNetv3 samll and MobileNetv3 large • Uses for balance of accuracy & speed
6	YOLOv5	• Built in model configuration file • Hyper parameters configuration file • Test time augmentation • Export to other file formats
7	SVM	• Support vector machine • Works well for multidimensional data • Used for both regression and classification • Uses vectors to create hyper plane for segregation
8	VGG16	• Uses 16 layers deep neural network • Rich training with million images • Input size- 224*224
9	SSIM	• Structural similarity index • Overcome Data compression and data transmission • Used in video industry, still photography
10	MobileNetv2	• 53 layers of deep neural network • Rich training with million images • Input size- 224*224
11	Convo 2D	• Creates convolution layers • Convolute with i/p layer • Give output tensor
12	ImageNet	• 14 million images • Visual object recognition software • Bounding boxes • 20000 categories
13	ShuffleNet	• A CNN used for mobile devices • For limited computer power 10-150 mflops • Point wise group convolution, channel shuffle • Reduce computation cost • Maintain accuracy
14	R-CNN inception	• Specification Metrics- type, mflops, mparams, source framework • Accuracy metrics- coco-precision,mAP
15	CSSNET	• Compressed Semantic segmentation method for hyper spectral images

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		• Based on shallow neural network • Dual-disperser CASSI • Spectral treatment + spectral spatial treatment
16	2D signal processing	• Deep frequency model for statistical signal processing • Alleviate over fitting problem • Used best for better ECG results

Comparison

Ref.	Network Type	Architecture	Training Type	Training Algorithm	Implementation Technique	Common Application	DL Framework
[1.]	Feedforward NN	CNN	Supervised	CSS-NET	Transfer Learning	Image Recognition/Classification	Tensorflow,Keras
[2.]	Feedforward NN	CNN	Supervised	YOLO-V3	Data Augmentation	Image Recognition/Classification	Tensorflow, Pytorch
[3.]	Feedforward NN	DCNN	Supervised	YOLO-V4	Faster RCNN	Object detection/Classification	SPPNET,Squuzeedet,cspnet
[4.]	Feature Pyramid Network	Deep ensemble CNN	Supervised	Hybrid YOLO-V2	Self-Adaption	Image Recognition/Classification	Keras, tensorflow
[5.]	Deep Physical NN	DNN	Supervised	Physics-Aware Training	Backpropogation	Physical/optical/electrical/mechanical classification	Tensorflow
[6.]	DNN	GNN,ANN,SNN	Supervised and Unsupervised	SVM	Self organising map, softmax layer	Localization/object detection	Keras/ pytorch
[7.]	FWD	CNN	Supervised	2D signal processing	Optimization	Image classification	Tensorflow
[8.]	PAFPN	CNN	Supervised	MobileNet-V2	Dual Attention Based Mechanism	Object detection	Keras

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[9.]	ANN	CNN	Supervised	SVM/AOI	Defect index matching	Object detection	Tensorflow
[10.]	CNN	CNN	supervised	YOLO	openCV	Edge detection/classification	Mechanized visual assessment
References	**Network Type**	**Architecture**	**Training Type**	**Training Algorithm**	**Implementation Technique**	**Common Application**	**Framework**
[11]	Inception Network	CNN	Supervised	Vgg16	Pre-trained feature extraction	Image processing	Tensorflow
[12]	Skip connected convolution autoencoder	CNN	UnSupervised	SSIM	Image Augmentation	Anomaly detection	keras
[13]	YOLO network	CNN	Semisupervised	YOLO	Robust data preprocessing	Target detection	Tensorflow/keras
[14]	DCNN	CNN	Supervised	Cnvo2D	Dropout	Image classification & object detection	Pytorch
[15]	Student teacher feature pyramid matching	CNN	Unsupervised	ImageNet	Distillation learning	Anomaly detection	Pytorch /STPM
[16]	Faster RCNN, MASK RCNN, FCN	CNN	Supervised ,unsupervised	shuffleNet	Transfer learning	Target detection	Pytorch /tensorflow
[17]	Pre-trained network	CNN	Supervised	R-CNN inception	Data augmentation	Component recognition	Keras
[18]	UNET	CNN	Supervised	MV2mobilenet	Data augmentation	Anomaly detection	Keras
[19]	PANET Path aggregation net	CNN	Supervised	YOLOV-5	Cross validation	Defect detection	Tensorflow/keras
[20]	Neck prediction network	CNN	Supervised	YOLOV4-MN3	Csp net	Defect detection	Pytorch

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Conclusion

A detailed overview has been provided about the neural networks and deep neural networks. We also have gone deep down into training algorithms and architectures and highlighted their drawbacks, pros and cons e.g. specific problems, over fitting, larger training time, Accuracy, speed of computation etc.

We have examined many of the state of art ways to get over with the present shortcomings of networks. We have conducted investigation about learning rates, hyper parameter tuning, and optimization of model. To summarize the content in precise manner a comparison table is also been added so that an overview of all the research papers can be reviewed in a glimpse.

True potential of deep learning has not been reached yet. There is enough room for tweaking the pre existed parameters and improvement of algorithms and further research for optimization and greater accuracy of architecture.

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